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Aluminum Consumption and Economic Growth: Evidence from Rich Countries

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The article attempts to test the aluminum consumption–economic growth nexus for 20 rich economies for the period 1970–2009. Various panel data unit root and cointegration tests are applied. The series are found to be integrated of order one and cointegrated, especially after controlling for cross-sectional dependence. Moreover, the Blundell–Bond system generalized methods-of-moments is employed to conduct a panel causality test in a vector error-correction mechanism setting. Unidirectional causality running from aluminum consumption to real GDP is uncovered in the short-run, while real GDP is found to Granger-cause aluminum consumption in the long-run. Moreover, a 1% increase in real GDP generates an increase of 0.44% in aluminum consumption in the long-run for the whole panel.

KEY WORDS: aluminum consumption, economic growth, panel causality, panel DOLS.

INTRODUCTION

Aluminum is one of the most important materials used today. Aluminum's strength, lightness, and malleability have led its increased applications in various sectors such as building, transport, and household. Such material is used in the manufacturing of frames, doors, railways, cars, cooking utensils, electrical appliances, etc., and has countless applications. The aluminum industry consists of four main areas of activity: bauxite mining, alumina refining, aluminum smelting, and fabrication/semi-fabrication of final products. However, the industry is extremely energy-intensive and its activities raise significant environmental concerns such as the creation of greenhouse gases (GHGs). First, using bauxite to produce alumina involved the discarding of chemical wastes (e.g., caustic soda) in landfills. GHGs and particles from boilers result from the production of alumina (Menzie et al. 2010). The processing of alumina to aluminum metal occurs in smelters via the Hall–Heroult process. This typically involves the dissolving of alumina in a bath of molten cryolite and transmitting an electric current through the solution, via a carbon anode and a carbon-lined metallic cathode. In addition to the enormous amount of electricity consumed, this process leads to the release of significant amounts of GHGs including perfluorocarbons: tetrafluoromethane (CF_4), hexafluoroethane (C_2F_6), and carbon dioxide (CO_2) emissions (Turton 2002).

The consumption of a metal such as aluminum can be considered intrinsically linked to the level of economic activity. From the policymaker's standpoint, it is vital to address the environmental issues emanating from the manufacture of aluminum and to discern whether any policy prescriptions will adversely affect

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economic activity levels. Furthermore, the price of aluminum necessarily dictates consumption of the material. Imposing a carbon tax scheme on smelters will eventually lead to an increase in aluminum prices as the cost of production rises. This can have an adverse effect on economic growth. This article presents the first study of the link between aluminum consumption and economic growth using panel data from 20 rich countries[3] over the period of 1970–2009. Demand for aluminum in high-income economies is more substantial than in low- or middle-income ones and any policies dealing with the aluminum industry are bound to have a more significant impact on economic growth and vice versa. Thus far, the literature has focused on cross-sectional or time-series studies. Refined aluminum consumption data are obtained from the World Bureau of Metal Statistics (various years), while those of real gross domestic product (GDP, at constant 2000) are gathered from the World Development Indicators CD-ROM (2011).

The remainder of this article is organized as follows: "Review of Literature" section reviews the literature. "The Testing Framework" section discusses the testing framework, which involves a three-stage procedure (Ghosh 2006) to test for any causality between the two variables. In the first stage, various panel unit root tests are performed to identify the order of integration of the two series. Depending on the results of these tests, the second stage consists of investigating any long-run relationship between the two series. Various panel cointegration tests will be conducted. Conditional on the outcome of the second stage, the third stage will consist of carrying out a panel vector error-correction mechanism (VECM)-based causality test using the two-step system generalized methods-of-moments (GMM) approach. The empirical results show strong evidence of a long-run relationship between aluminum consumption and economic growth and, a long-run causal effect of economic growth on aluminum consumption is also uncovered. "Conclusion and Policy Implications" section concludes and discusses the policy implications of this study.

REVIEW OF LITERATURE

The literature on the link between metal consumption and economic growth remains relatively sparse. Tilton (1989) analyzes six industrial metals in the OECD, the US, Japan, and the EEC over two periods, 1960–1973 and 1973–1985. Metal consumption in these regions is found to be stimulated by increased economic activity. Roberts (1990) forecasts the US steel consumption up to 2010 using data over the period 1963–1983. He notes the importance of the gross national product in determining metal use. Labson and Crompton (1993) analyze the link between five industrial metals and income for the US, UK, Japan, and OECD for the period of 1960–1987. However, they offer little evidence to support the presence a long-run link between the two variables.

Recently, Ghosh (2006) has examined cointegration and Granger causality between steel consumption and economic growth in India for the period beginning in 1951–1952 and ending in 2003–2004 through a vector autoregression (VAR) structure. He does not find evidence of cointegration but he discovers the existence of a unidirectional causal effect of economic growth on steel consumption. Huh (2011) studies the short- and long-run causal links between steel consumption and economic activity in Korea over the period of 1975–2008 using VECM and VAR models. Using disaggregated data, he uncovers a long-run relationship between total steel consumption and GDP. Furthermore, a unidirectional causality running from GDP to total steel consumption is detected. Evidence of a long-run bidirectional causality between flat products consumption and manufacturing GDP is also found. Next, flat products consumption is found to have a long-run relationship with steel-consuming industries such as the automobile, shipbuilding, and fabricated metal product industries, but with mixed causal directions, depending on variable pairs. According to his study, steel and steel-consuming industries are expected to have a significant impact on economic growth.

THE TESTING FRAMEWORK

To investigate whether economic growth has an impact on aluminum consumption the following reduced-form equation can be estimated:

$$\mathrm{LALC}_{it} = \beta_0 + \beta_1 \mathrm{LGDP}_{it} + \varepsilon_{it} \tag{1}$$

where LALC_{it} denotes the natural logarithm of refined aluminum consumption (in metric tonnes) for country i over year t. LGDP_{it} measures real

[3]The time frame and the selection of countries are purely dictated by the availability of data. The rich economies follow the classification of the World Bank (at http://go.worldbank.org/K2CKM78CC0).

income or economic growth and denotes the natural logarithm of GDP (at constant 2000) for country i and year t. β_0 is the constant term. β_1 illustrates the income elasticity of aluminum consumption for the panel as a whole group of 20 high-income countries. The resulting elasticity may not coincide with the elasticity at individual levels. If $\beta_1 > 1$, this depicts a high responsiveness of aluminum consumption to changes in income. A rise in real GDP leads to a more than proportionate rise in aluminum consumption. Aluminum is deemed to be a luxury good. If $0 < \beta_1 < 1$, then a rise in real GDP leads to a less than proportionate rise in aluminum consumption. Aluminum is deemed to be a normal good. If $\beta_1 < 0$, then a rise in real GDP leads to a fall in aluminum consumption. Aluminum is deemed to be an inferior good. ε_{it} is the error-term. Table 1 shows the trends of $LALC_{it}$ and $LGPD_{it}$ over selected years.

Panel Unit Root and Cointegration Tests

Preliminary tests such as unit root and cointegration tests are necessary before carrying out a panel VECM-based causality test. Practically, most of the panel unit root tests are based on an augmented Dickey–Fuller (ADF 1979) unit root test type:

$$\Delta y_{it} = \mu_i + \beta_i t + \rho y_{it-1} + \alpha_{im} \sum_{m=1}^{k_i} \Delta y_{i,t-m} + e_{it} \quad (2)$$

where $\Delta y_{it} = y_{it} - y_{it-1}$, t is the time trend, k is the lag length, and e is the error-term. If the null hypothesis (H_0) is accepted (i.e., H_0: $\hat{\rho} = 0$), then the series is non-stationary. The unit root tests used are Levin, Lin, and Chu (LLC 2002), Im, Pesaran, and Shin (IPS 2003), Hadri (2000), Im, Lee, and Tieslau (ILT 2005), and Pesaran (2007) tests. These tests exhibit some statistical shortcomings in terms of size and power properties. To present robust evidence about the order of integration of the series, it is therefore more practical to perform several tests before reaching a conclusion.

Next, if both series are non-stationary and integrated of the same order, panel cointegration tests can be performed. Nyblom and Harvey (NH 2000) put forth a test of common trends where H_0 is the stationarity of the series around a deterministic trend, where there exists $k < n$ common trends (where rank $(\Sigma\eta) = k$), against the alternative of a random walk component occurrence where there

Table 1. Trends Over Selected Years

	LALC				LGDP				LURB			
Countries	1970	1995	2009	1970–2009	1970	1995	2009	1970–2009	1970	1995	2009	1970–2009
Australia	11.730	12.746	12.651	12.520	25.800	26.545	27.030	26.468	0.487	0.855	1.046	0.791
Austria	11.225	11.918	12.207	11.923	25.157	25.829	26.109	25.738	4.501	4.569	4.620	4.550
Belgium	12.072	12.724	12.516	12.612	25.421	26.031	26.287	25.947	5.763	5.813	5.876	5.805
Canada	12.301	13.324	13.395	13.105	26.387	27.107	27.465	27.033	0.867	1.172	1.311	1.108
Denmark	9.127	10.240	10.788	10.256	25.115	25.658	25.853	25.569	4.756	4.814	4.870	4.809
Finland	9.836	10.342	10.266	10.151	24.649	25.290	25.675	25.278	2.716	2.794	2.794	2.820
France	12.932	13.520	13.178	13.350	27.119	27.776	28.018	27.691	4.529	4.660	4.739	4.636
Greece	10.285	12.000	12.736	11.831	24.807	24.807	25.844	25.395	4.223	4.413	4.472	4.367
Hungary	11.427	11.703	11.901	12.063	23.910	24.388	24.792	24.481	4.744	4.744	4.717	4.750
Italy	12.539	13.408	13.403	13.298	26.956	27.630	27.738	27.508	5.209	5.264	5.322	5.262
Japan	13.723	14.664	14.626	14.462	28.165	29.124	29.214	28.928	5.651	5.841	5.858	5.802
Netherlands	10.870	11.918	11.894	11.696	25.837	26.478	26.790	26.397	5.956	6.127	6.194	6.092
New Zealand	9.496	10.565	11.275	10.542	24.009	24.534	24.874	24.476	2.371	2.636	2.797	2.588
Norway	11.204	11.964	12.101	11.984	24.779	25.668	26.010	25.551	2.545	2.662	2.760	2.643
South Korea	9.636	13.423	13.780	13.005	24.877	26.788	27.347	26.536	5.779	6.124	6.221	6.058
Spain	11.768	12.766	13.105	12.747	26.166	26.886	27.294	26.832	4.213	4.368	4.523	4.358
Sweden	11.273	11.661	10.806	11.564	25.613	26.061	26.384	26.031	2.976	3.069	3.121	3.041
Switzerland	11.433	11.905	11.874	11.843	25.796	26.143	26.380	26.092	5.054	5.171	5.264	5.137
United Kingdom	12.910	13.337	12.506	12.972	27.312	27.852	28.153	27.787	5.438	5.480	5.544	5.474
USA	15.065	15.436	15.170	15.392	28.950	29.711	30.061	29.619	3.109	3.370	3.513	3.318

The average figure is computed for the period 1970–2009.
Source Computed.

exists more than k common trends (where rank $(\Sigma\eta) > k$). In addition, Pedroni (1999, 2004) suggests seven tests with the H_0 of no cointegration. Four of these statistics are called panel cointegration statistics. These are panel-v, panel-ρ, and panel-pp which denote the non-parametric variance ratio, Phillips-Perron ρ, and Student's t statistics, respectively, while panel-adf is a parametric statistic based on the ADF-statistic. The extra three statistics are called group mean panel cointegration statistics. These are the group-ρ, group-pp, and group-adf which correspond to Phillips-Perron ρ-statistic, Phillips-Perron t-statistic, and the ADF-statistic, respectively. The three statistics allow the modeling of potential heterogeneity across the panel.

The two cointegration tests assume cross-sectional independence in the error-term. Such an assumption is unlikely to hold in practice. Westerlund (2007) suggests four panel tests of the H_0 of no cointegration, which allows for cross-sectional dependence. The panel tests denoted by Gt and Ga are performed under the alternative hypothesis of panel cointegration, while Pt and Pa are performed under the alternative hypothesis that at least one element of the panel is cointegrated. The H_0 of no cointegration which assumes that the error-correction term in a conditional error-correction model is equal to zero is tested. If the H_0 of no error-correction is supported, the H_0 of no cointegration is accepted. If the series are cointegrated, causality should run in at least one direction (Engle and Granger 1987).

The panel unit root tests are performed with two different regressions. One regression includes a constant term only, while the other contains both a constant term and a time trend. A macroeconomic series typically exhibits a trend over time and is non-stationary. It is thus more appropriate to consider a regression with a constant and a trend at level form. First-differencing can be used to remove any deterministic trends in the series. Hence, regressions should contain a constant term only. For the sake of comparison, both deterministics are computed. Failure to test for a unit root and cointegration can lead to spurious results. This underlines the importance of performing these vital tests. Let a time-series variable, say $LALC_t$, be integrated order of d, i.e., $LALC_t \sim I(d)$, if it were to be differenced by d times to become stationary.

The ADF unit root statistics for individual countries are reported in Tables 2 and 3. The series tends to support the above-discussed a priori expectation regarding the order of integration expected for Belgium, New Zealand, Sweden, Switzerland, and the United Kingdom. The series for these countries are found to be non-stationary. One major problem arising with time-series tests is the lack of observations over reasonably long periods. As argued by Toda (1995), even 100 observations are not enough to ensure good performance of the time-series tests. These are as a consequence subject to the criticism of low power. One solution is to apply panel data tests which allow for a sizeable increase in testing power of the framework.

In Table 4, the LLC test statistics for both series are presented, where $LALC_{it} \sim I(0)$ and $LGDP_{it} \sim I(1)$. However, the LLC assumptions are restrictive. The test is based on the assumption of homogeneity in the autoregressive of order one (AR(1)) coefficients of the ADF specifications. Other tests, controlling for heterogeneity, structural break or cross-sectional dependence are essential to truly evaluate the order of integration of $LALC_{it}$ and $LGDP_{it}$. According to Banerjee et al. (2004), cross-sectional dependence biases the panel data unit root tests towards the alternative hypothesis. The degree of cross-sectional dependence can be studied by examining the pair-wise correlations between changes in the variables (Koedijk et al. 2004). The pair-wise correlations of the first-differences in two series are generally positive and rather large.[4] For instance, the pair-wise correlation of $\Delta LALC_{it}$ between Austria and Italy is 0.5328 and for Belgium and Switzerland, it is 0.59593. The pair-wise correlations of $\Delta LALC_{it}$ range from -0.0890 to 0.9093. In addition, the pair-wise correlation of $\Delta LGDP_{it}$ between Denmark and the Netherlands is 0.5487, while the correlation coefficient between France and Spain is calculated to be 0.7943. The pair-wise correlation of $\Delta LGDP_{it}$ ranges from -0.0619 to 0.8434. Therefore, cross-sectional dependence has key implications for the testing framework.

IPS (2003) and Hadri (2000) both recommend a test which allows for heterogeneity between groups. Their tests control for cross-sectional dependence using demeaned data. The IPS test has low power in panels with small T (Karlsson and Löthgren 2000), while the reverse is true for the Hadri test (Barhoumi 2005). As shown in Table 5, the IPS generates similar results to the LLC concerning the order of integration. The Hadri test statistics are reported in

[4]Detailed results of the pair-wise correlations are available upon request.

Table 2. ADF-Statistics for Individual Countries at Level Form

	$LALC_{it}$				$LGDP_{it}$			
	With Constant and Without Trend		With Constant and With Trend		With Constant and Without Trend		With Constant and With Trend	
Countries	ADF	ρ	ADF	ρ	ADF	ρ	ADF	ρ
Australia	−2.376‡	0	−1.733	0	0.607	0	−2.343	0
Austria	−1.456	0	−2.828	0	−1.114	0	−3.049	0
Belgium	−2.059	0	−4.355*	2	−1.009	0	−2.696	0
Canada	−1.071	0	−2.029	0	−1.094	1	−2.573	1
Denmark	−3.356**	1	−2.392	1	−1.071	0	−2.312	1
Finland	−1.558	1	−2.454	0	−1.251	2	−2.008	2
France	−2.606	2	0.4360	2	−1.579	1	−1.671	1
Greece	−1.382	2	−3.451	0	0.725	0	−1.168	0
Hungary	−2.113	0	−1.886	0	−1.791	1	−2.430	1
Italy	−1.657	0	−2.632	0	−3.296**	0	0.0722	0
Japan	−1.597	2	−1.274	2	−2.070	1	0.809	2
Netherlands	−1.350	1	−2.314	1	−0.774	1	−2.072	1
New Zealand	−0.805	0	−2.787	0	0.298	1	−3.392‡	2
Norway	−1.377	0	−2.769	0	−2.356	2	−1.245	2
South Korea	−2.109	1	−0.703	1	−2.514	0	0.087	2
Spain	−1.174	3	−1.710	0	−0.447	1	−3.177	1
Sweden	−2.502	0	−1.420	1	−0.399	2	−3.286‡	1
Switzerland	−1.921	0	−2.961	0	0.567	2	−4.713*	1
United Kingdom	−0.719	1	−0.602	1	−0.595	2	−3.682**	1
USA	−2.369	0	−2.801	0	−0.817	2	−2.772	1

To select the order of lag ρ, we start with a maximum lag length of three and pare it down as per the Akaike Information Criterion (AIC). There is no general rule on how to choose the maximum lag to start with. The bandwidth and maximum lag length are chosen according to the Bartlett kernel which is equal to $4(T/100)^{2/9} \approx 3$, where $T = 40$ (Basher and Westerlund 2008). The MacKinnon (1991) one-sided critical values for the ADF unit root tests with a constant and without a time are −3.682, −2.972, and −2.618 at 1, 5, and 10% significance levels, respectively, while those with a constant and a time trend are −4.279, −3.556, and −3.214, respectively.
Source Computed.
*, **, and ‡ denote 1, 5, and 10% significance levels, respectively.

Table 6. These show $LALC_{it} \sim I(1)$ while $LGDP_{it}$ is integrated of an order higher than one. Following Caner and Kilian (2001), unit root tests for the H_0 of stationarity tend to have serious size distortions when the H_0 is close to the alternative of a unit root. Moreover, Choi (2001) argues about the loss of power of the LLC and IPS tests when a linear trend is included and proposes some alternative tests. Referring to especially the Z and L^* statistics in Table 7, both series tend to be $I(1)$. Furthermore, endogenous structural breaks can cause a loss in power to reject a unit root even if the trend stationarity alternative is true (Perron 1989). ILT (2005) present a test to account for endogenous structural breaks. As reported in Table 8, both variables are $I(0)$.

However, all these first-generation tests tend to suffer from size distortions and have low power in the presence of cross-sectional dependence (Herwartz and Siedenburg 2008). This can lead to incorrect inference. The IPS, Choi, and Hadri tests control for cross-sectional dependence using demeaned data. Assuming the existence of one common factor with the same effect on all the individuals and as such is rather restrictive. Furthermore, according to Strauss and Yigit (2003), the demeaning of data may not get rid of the size problem. Even the ILT test fails to efficiently allow for cross-sectional dependence as occurs with the test of IPS, Choi, and Hadri. Pesaran (2007) proposes a second-generation test which allows for the presence of more general cross-sectional dependence patterns. To control for cross-sectional dependence, the standard ADF regression models are augmented with the cross-section averages of lagged levels and first-differences of the individual series. This test is based on the averages of the individual cross-sectionally augmented ADF (CADF) statistics and is found to have good size and power properties even when N and T are relatively small. As reported in Table 9, both variables are found to be $I(1)$. Cointegration tests can be carried out.

Table 3. ADF-Statistics for Individual Countries at First-Difference

	$LALC_{it}$				$LGDP_{it}$			
	With Constant and Without Trend		With Constant and With Trend		With Constant and Without Trend		With Constant and With Trend	
Countries	ADF	ρ	ADF	ρ	ADF	ρ	ADF	ρ
Australia	−6.648*	0	−6.215*	1	−5.371*	0	−5.428*	0
Austria	−4.711*	0	−4.616*	0	−4.829*	1	−4.824*	1
Belgium	−5.058*	0	−5.007*	0	−6.358*	1	−6.290*	1
Canada	−7.191*	0	−7.080*	0	−3.520**	0	−3.585**	0
Denmark	−3.499**	1	−6.627*	0	−3.758*	0	−3.820**	0
Finland	−8.434*	0	−8.316*	0	−3.480**	1	−3.388‡	1
France	−2.403	2	−6.457*	1	−3.907*	0	−4.134**	0
Greece	−6.897*	0	−3.645**	2	−1.954	2	−1.758	2
Hungary	−4.988*	0	−4.953*	0	−2.457	0	−2.444	0
Italy	−6.087*	0	−6.093*	0	−4.187*	0	−5.352*	0
Japan	−6.527*	1	−6.678*	1	−1.823	0	−3.509‡	0
Netherlands	−7.177*	1	−7.062*	1	−3.210**	0	−3.112	0
New Zealand	−5.362*	3	−5.501*	3	−4.611*	3	−5.209*	3
Norway	−3.573*	3	−3.659*	3	−2.996**	1	−3.757**	1
South Korea	−6.928*	0	−7.812*	0	−4.301*	0	−5.010*	0
Spain	−2.047	2	−2.005	2	−2.357	0	−2.240	0
Sweden	−6.219*	0	−6.071*	0	−3.176**	1	−2.984	1
Switzerland	−7.267*	0	−7.178*	0	−4.770*	1	−4.922*	1
United Kingdom	−9.301*	0	−9.270*	0	−3.171**	1	−2.742	1
USA	−4.619*	3	−4.549*	3	−3.638**	0	−3.680**	0

MacKinnon (1991) critical values for the ADF unit root tests with a constant and without a time are −3.682, −2.972, and −2.618 at 1, 5, and 10% significance level, respectively, while those with a constant and a time trend are −4.288, −3.560, and −3.216, respectively.
Source Computed.

Table 4. LLC Panel Unit Root Test Statistics

		Level Form		First-Difference	
Variables	Deterministics	t Value	t*	t Value	t*
$LALC_{it}$	Constant	−5.750	−1.6136 [0.053]‡	−32.995	−27.027 [0.000]*
	Constant + trend	−11.580	−2.4869 [0.006]*	−31.139	−22.212 [0.000]*
$LGDP_{it}$	Constant	−4.843	−1.512 [0.065]‡	−19.241	−13.467 [0.000]*
	Constant + trend	−8.036	−1.1039 [0.135]	−21.172	−13.561 [0.000]*

These statistics are distributed as standard normal as both N and T grow large. Assuming no cross-country correlation and T is the same for all countries, the normalized t* test statistic is computed using the t value statistics. After transformation by factors provided by LLC, the t* tests is distributed standard normal under the H_0 of non-stationarity. It is then compared to the 1, 5, and 10% significance levels with the one-sided critical values of −2.326, −1.645, and −1.282, respectively. The p values are in square brackets.
Source Computed.

In Table 10, the NH panel cointegration test statistics are computed under both the independent and the identically distributed (iid) random walk (RW) errors (NH-t) and the serially correlated residuals (NH adj-t) assumptions. H_0 of no cointegration is rejected under both specifications. Subsequently, the Pedroni cointegration test statistics are computed and presented in Table 11. All these test statistics reveal a clear rejection of H_0. Nonetheless, analogous to panel unit root tests, panel cointegration tests can also be affected by the prevalence of cross-sectional dependence. The Westerlund cointegration test can effectively control cross-sectional dependence through bootstrapping. This can be considered as a second-generation cointegration test. Table 12 indicates a rejection of H_0 when referring to the Gt and Pt statistics. In general, a long-run relationship between $LALC_{it}$ and $LGDP_{it}$ is confirmed.

Table 5. IPS Panel Unit Root Test Statistics

Variables	Data	Deterministics	Level Form t-Bar	Level Form Ψ_t	First-Difference t-Bar	First-Difference Ψ_t
$LALC_{it}$	Raw	Constant	−1.916	−2.035 [0.021]**	−6.223	−23.651 [0.000]*
		Constant + trend	−2.421	−1.390 [0.082]‡	−6.198	−21.930 [0.000]*
	Demeaned	Constant	−1.750	−1.206 [0.114	−6.919	−27.142 [0.000]*
		Constant + trend	−2.676	−2.785 [0.003]*	−6.494	−23.538 [0.000]*
$LGDP_{it}$	Raw	Constant	−1.529	−0.107 [0.457]	−3.663	−10.806 [0.000]*
		Constant + trend	−2.254	−0.502 [0.308]	−4.021	−10.098 [0.000]*
	Demeaned	Constant	−1.260	1.240 [0.892]	−4.226	−13.637 [0.000]*
		Constant + trend	−2.061	0.546 [0.707]	−4.611	−13.317 [0.000]*

The IPS test statistics are computed as the average ADF-statistics across the sample. These statistics are distributed as standard normal as both N and T grow large. t-bar is the panel test based on the ADF-statistics. The lag lengths for the panel test are based on those employed in the univariate ADF test. Critical values for the t-bar statistics without trend at 1, 5, and 10% significance levels are −1.980, −1.850, and −1.780 while with inclusion of a time trend, the critical values are −2.590, −2.480, and −2.410, respectively. Assuming no cross-country correlation and T is the same for all countries; the normalized Ψ_t test statistic is computed by using the t-bar statistics. The Ψ_t tests for H_0 of joint non-stationarity and is compared to the 1, 5, and 10% significance levels with critical values of −2.330, −1.645, and −1.282, respectively. The p values are in square brackets.
Source Computed.

Table 6. Hadri Panel Unit Root Test Statistics

Variables	Data	Deterministics	Level Form Z	Level Form p value	First-Difference Z	First-Difference p value
$LALC_{it}$	Raw	Constant	24.8602	0.0000*	0.7167	0.2368
		Constant + trend	9.7939	0.0000*	2.1768	0.0147**
	Demeaned	Constant	22.3960	0.0000*	−1.2840	0.9004
		Constant + trend	10.0568	0.0000*	1.6709	0.0474**
$LGDP_{it}$	Raw	Constant	27.5120	0.0000*	4.1106	0.0000*
		Constant + trend	12.6745	0.0000*	3.724	0.0001**
	Demeaned	Constant	24.8446	0.0000*	3.1707	0.0008**
		Constant + trend	13.8067	0.0000*	4.8507	0.0000**

The Z test is based on the Lagrange Multiplier (LM) tests are based on the average of the N country-specific KPSS LM-statistics (Kwiatkowski et al. 1992) under which the H_0 of stationarity is tested. The Bartlett kernel is chosen to be 3. Heteroskedasticity is controlled while computing the statistics.
Source Computed.

Panel VECM-Based Causality Test

Next, any causal relationships between refined aluminum consumption and economic growth are investigated. The key question for determining causal relationships is whether income boosts aluminum consumption or aluminum consumption itself is a stimulus for economic growth via indirect channels of effective demand or supply. One of these channels[5] can be the degree of urbanization. For instance, as urban centers grow, the demand for more housing tends to rise, and this in turn boosts infrastructural demand for goods such as pipes for water, window frames, electricity cables, etc. (Farooki 2010). Thus, the level of urbanization can affect aluminum consumption. However, urbanization can also be connected to economic growth. According to Abdel-Rahman et al. (2006), nations with highly developed infrastructure and advanced technology will tend to be highly urbanized. Urbanization can be used as an instrumental variable (IV) to capture any indirect channel. Table 1 describes the trend of the natural logarithm of population density (LURB) across countries.

Understanding how a change in economic growth affects aluminum consumption is vital in policy formation. It is therefore necessary to examine any causal relationship between these two variables.

[5]Subject to data availability, other instruments such as consumption of durable goods (e.g., appliances) and non-durables (e.g., packaging), etc., could have been considered.

Table 7. Choi Panel Unit Root Test Statistics

Variables	Data	Deterministics	Level Form Z	Level Form L^*	Level Form P_m	First-Difference Z	First-Difference L^*	First-Difference P_m
$LALC_{it}$	Raw	Without trend	−0.1314 [0.4477]	−0.1614 [0.4361]	−0.4037 [0.6568]	−9.1378 [0.0000]*	−10.8329 [0.0000]*	15.5813 [0.0000]*
		With trend	1.6644 [0.9520]	1.7338 [0.9570]	−0.6252 [0.7341]	−9.6755 [0.0000]*	−11.3558 [0.0000]*	16.2688 [0.0000]*
	Demeaned	Without trend	−0.4982 [0.3092]	−0.9196 [0.1800]	1.5287 [0.0632]‡	−9.6755 [0.0000]*	−11.3558 [0.0000]*	16.2688 [0.0000]*
		With trend	−0.1445 [0.4426]	−0.4865 [0.3138]	0.6313 [0.2639]	−7.4199 [0.0000]*	−8.8289 [0.0000]*	12.2887 [0.0000]*
$LGDP_{it}$	Raw	Without trend	3.1964 [0.9993]	3.3337 [0.9994]	−2.0407 [0.9794]	−6.5052 [0.0000]*	−7.1225 [0.0000]*	9.4527 [0.0000]*
		With trend	1.0285 [0.8481]	1.2709 [0.8967]	0.0135 [0.4946]	−5.3953 [0.0000]*	−5.8493 [0.0000]*	7.3811 [0.0000]*
	Demeaned	Without trend	0.1009 [0.5402]	0.1505 [0.5597]	1.3055 [0.0959]‡	−7.5527 [0.0000]*	−8.5168 [0.0000]*	11.6840 [0.0000]*
		With trend	−0.9613 [0.1682]	−0.9347 [0.1760]	2.5098 [0.0060]*	−6.6210 [0.0000]*	−7.4852 [0.0000]*	9.9078 [0.0000]*

The tests are based on the p values obtained from the ADF tests applied to the individual series. All test statistics are asymptotically distributed as $N(0,1)$. The Z test is an inverse normal test. The L^* test is a modified logit test. The P_m test is a modified Fisher's inverse χ^2 test. All statistics have a standard normal distribution under H_0 when T and N tend to infinity. The null hypothesis of non-stationarity is rejected when P_m is greater than the upper tail of the standard normal distribution. For other two tests, the null is rejected when the computed statistics are inferior to the lower tail. The p values are in square brackets.
Source Computed.

Usually, economic theory offers a basis to construct econometric models and to empirically test them. However, support from the theoretical point of view may not be sufficiently available. As such, one methodology which has been extensively applied in the literature is the Granger causality test. Indeed, as stated by Farr et al. (1998), "… Granger results do provide valuable information that can aid in the development of new theories or in the refinement of existing ones." A Granger causality test requires the variables to be stationary. Hence, an ECM-based VAR causality test which makes use of the first-differenced stationary data will be performed. This also allows for the investigation of any short- or long-run causal relationship.

The ρth order of the panel VECM structure for the causality test (Jaunky 2011) can be represented as follows:

$$\begin{bmatrix} \Delta LALC_{it} \\ \Delta LGDP_{it} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \sum_{k=1}^{\rho} \begin{bmatrix} \beta_{11k} & \beta_{12k} \\ \beta_{21k} & \beta_{22k} \end{bmatrix} \begin{bmatrix} \Delta LALC_{it-i} \\ \Delta LGDP_{it-i} \end{bmatrix} + \begin{bmatrix} \phi_1 \\ \phi_2 \end{bmatrix} [ECM_{it-1}] + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \quad (3)$$

where $i=1,\ldots,N$; $t=\rho+2,\ldots,T$; The αs, β_ks, and φs are parameters to be estimated. ECM_{it-1} represents the one period lagged error-term derived from the cointegrating vector and the error-terms ε_1 and ε_2, are serially independent with mean zero and finite covariance matrix. Given the use of a VAR structure, all variables are treated as endogenous variables. A simple Wald test for joint significance can be conducted to determine the direction of any causal relationship between the two variables. The results from this test should be interpreted as indicating whether prior changes in one variable contribute (or do not contribute) significantly to the prediction of the future value of the other variable. In this case, economic growth does not Granger-cause aluminum consumption if and only if all of the coefficients β_{12k}; $\forall=1,\ldots,\rho$ are not significantly different from zero in Eq. 3. The dependent variable reacts only to short-term shocks. In the same way, aluminum consumption does not Granger-cause economic growth in the short-run if and if all of the coefficients β_{21k}; $\forall=1,\ldots,\rho$ are not significantly different from zero. These are referred to as the "short-run Granger causality" tests. The coefficients on the ECTs represent how fast deviations from the long-run equilibrium are eliminated. Another

Table 8. ILT Panel LM Unit Root Test Statistics

Variables	Without Break	With One Break	With Two Breaks
$LALC_{it}$	−4.576*	−8.929*	−10.997*
$LGDP_{it}$	−3.056*	−7.128*	−8.108*

Critical values for the LM panel unit root test (without or with breaks) are distributed asymptotic standard normal and are −2.326, −1.645, and −1.282 at the 1, 5, and 10% levels, respectively. The minimum LM unit root test which accounts for a break in the data is employed to test for the H_0 of non-stationarity. Time dummies are included when performing the panel unit root test in the presence of one structural break. The Bartlett kernel is used for the maximum lag length.
Source Computed.

Table 9. Pesaran CADF Panel Unit Root Test Statistics

		Level Form		First-Difference	
Variables	Deterministics	*t*-Bar	*Z*	*t*-Bar	*Z*
$LALC_{it}$	Constant	−2.572	−3.815 [0.000]*	−5.286	−16.726 [0.000]*
	Constant + trend	−2.507	−0.849 [0.198]	−5.243	−14.753 [0.000]*
$LGDP_{it}$	Constant	−1.874	−0.493 [0.311]	−4.287	−11.975 [0.000]*
	Constant + trend	−2.051	1.467 [0.929]	−4.639	−11.686 [0.000]*

The Pesaran CADF test of the H_0 of non-stationarity is based on the mean of individual DF (or ADF) *t*-statistics of each unit in the panel. To remove the cross dependence, the standard DF (or ADF) regressions are augmented with the cross-sectional averages of lagged levels and first-differences of the individual series (CADF-statistics). Critical values for the *t*-bar statistics without and with trend at 1, 5, and 10% significance levels are −2.360, −2.200, and −2.110; and −2.850, −2.710, and −2.630, respectively. Assuming cross-sectional dependence and *T* is the same for all countries. The normalized *Z* test statistic is computed using the *t*-bar statistics. The *Z* test statistic is compared to the 1, 5, and 10% significance levels with the one-sided critical values of −2.326, −1.645, and −1.282, respectively.
Source Computed.

Table 10. Nyblom–Harvey Panel Cointegration Test Statistics

Specifications	Statistics	LAINT	LGDP
Fixed-Effects	NH-*t*	10.8162*	11.2894*
	NH adj-*t*	22.4711*	20.8405*
Fixed-Effects and Time Trends	NH-*t*	10.8792*	11.3603*
	NH adj-*t*	28.5619*	24.8268*

The H_0 of the test is no cointegration (H_0: rank(var–cov) = $K = 0$) against the alternative hypothesis of cointegration (H_1: rank(var–cov) = $K \neq 0$). H_0: 0 common trends among the 36 series in the panel. *NH-t* the test is performed under the hypothesis of iid errors, *NH adj-t* errors are allowed to be serially correlated and the test is performed using an estimate of the long-run variance derived from the spectral density matrix at frequency zero. The number of lags of the non-parametric adjustment for long-run variance is equal to 2. No model needs to be estimated as the test is based on the rank of covariance matrix of the disturbances resulting from the multivariate random walk. Critical values for the *t*-bar statistics without and with trend at 1, 5, and 10% significance levels are 5.1142, 4.4957, and 4.1794; and 1.8425, 1.5798, and 1.6651, respectively.
Source Computed.

channel of causality can be investigated by testing the significance of the ECTs. This test is known to as the ''long-run Granger causality'' tests.

The direction of causality between aluminum consumption and economic growth has significant policy implications. If there is no causality, then adopting a conservative resource policy measures to limit the consumption of aluminum can be implemented, without the concern of negatively impacting on economic growth. A fall in aluminum consumption can lead aluminum smelting industries to cut down production. This will eventually cause a reduction in the exploitation of natural resources and environmental degradation. This will cause a decline in the utilization of energy, such as electricity. If causality runs from economic growth to aluminum consumption, then environmental and resource policies can be implemented. For instance, carbon taxes and tariffs can be imposed on the aluminum smelting industries. These policies will have no impact on economic growth. However, if a unidirectional causality running from aluminum consumption to economic growth exists, then resource conservation policies will have an adverse impact on economic growth.

Conventional ordinary least squares (OLS), fixed-effects, or even random-effects methods tend to yield biased results due to the correlation between the lagged dependent variables and the error-terms. In order to specify the correlation and endogeneity problems, Arellano and Bond (1991) propose a two-step difference GMM method. In the first step, the residuals are assumed to be independent and homoskedastic. In the second step, the first step residuals are used to build consistent inference of variances and covariances matrixes while the former assumptions are relaxed. For the instruments to be valid there should not be serial correlation in ε_1 and ε_2. The optimal lag length, ρ, is selected until no serial correlation is found in the residuals. For disturbances to be serially uncorrelated there should be evidence of significant negative first-order serial correlation and no evidence of second-order correlation in the differenced residuals. However, the Arellano–Bond two-step GMM procedure does not work well internal instruments. When the lag of the dependent variable and the explanatory variables is persistent over time, lags of the levels of these variables are weak instruments for the equation in differences (Alonso-Borrego and Arellano 1999; Blundell and Bond 1998).

Arellano and Bover (1995) and Blundell and Bond (1998) advocate the two-step system GMM estimator because it has superior finite-sample properties. This estimator is a linear combination of the levels and differences and the weight specified to the levels estimators grows in the event of weak instruments due to high persistency in the series. In the presence of heteroskedasticity and serial correlation, the two-step GMM employs a consistent estimate of the weighting matrix, exploiting the residuals from the one-step estimator (Davidson and Mackinnon 2004). The former is more efficient than the one-step estimator. Yet, the former converges slowly to its asymptotic distribution, while its standard errors tend to be biased downwards for finite samples, in contrast to the one-step estimator. A solution is to use the finite-sample correction to the two-step covariance matrix (Windmeijer 2005). Thus, the two-step approach can still be considered.

The two-step system GMM allows for the use of IVs. Population density is used as a proxy to capture the level of urbanization (Hong and Chin 2007). In addition, time dummies are also employed as IVs to

Table 11. Pedroni Panel Cointegration Test statistics

Statistics	Without Trend	With Trend
Panel-v	7.59820*	4.54019*
Panel-ρ	−6.76174*	−5.53981*
Panel-pp	−5.09093*	−5.54941*
Panel-adf	−4.54669*	−4.90893*
Group-ρ	−5.73334*	−3.84260*
Group-pp	−5.14180*	−5.23626*
Group-adf	−4.77304*	−4.75988*

The panel statistics are the within-dimension statistics while group statistics are between-dimension ones. These are one-sided standard normal test with critical values of 1, 5, and 10% given by −2.326, −1.645, and −1.282. A special case is the panel-v statistic which diverges to positive infinity under the alternative hypothesis. Rejection of the H_0 of no cointegration requires values larger than 2.326, 1.645, and 1.282 at 1, 5, and 10% significance level, respectively. The critical values for the mean and variance of each statistic are obtained from Pedroni (1999). H_0 corresponds to no cointegration.
Source Computed.

Table 12. Westerlund Panel Cointegration Test statistics

	Without Trend				With Trend			
Statistics	Value	Z	p Value	Robust p Value	Value	Z	p Value	Robust p Value
Gt	−1.717	−3.185	0.001‡	0.002*	−2.899	−2.932	0.002*	0.011**
Ga	−4.202	−0.393	0.347	0.197	−10.492	0.999	0.841	0.541
Pt	−5.196	−2.495	0.006**	0.083‡	−12.789	−3.821	0.000*	0.044**
Pa	−2.182	−1.786	0.037**	0.194	−11.252	−1.692	0.045**	0.162

All these statistics are distributed standard normally. Critical values of one-sided tests for 1, 5, and 10% significance levels are −2.326, −1.645, and −1.282, respectively. The lag and lead lengths are set to one. Choosing too many lags and leads can result in a deterioration of the small-sample properties of the test. To control for cross-sectional dependence, robust critical values is obtained through 5,000 bootstrap replications.
Source Computed.

control for cross-sectional dependence (Roodman 2009). The IVs are assumed to be correlated with the regressors but uncorrelated with ε_1 and ε_2. Referring to the over-identifying restrictions, both the Hansen (1982) *J* test and the Sargan (1958) test are conducted. These tests test for the joint validity of the instruments to confirm whether the model specification is correct. The Sargan test is not robust to heteroskedasticity or autocorrelation while the Hansen test is. Using too many instruments can cause these tests to be weak. Too many weak instruments can overload the endogenous variables and decrease the accuracy of the Sargan and Hansen tests (Roodman 2009). A rule of thumb is to maintain the number of instruments at less than or equal to the number of groups (Docquier et al. 2011). Thus, the number of instruments used is set to 20, which is equivalent to the number of groups in the panel.

As shown in Table 13, negative first-order serial correlation in the disturbances is discovered in the first-differenced residuals. No second-order serial correlation is established. These results imply an absence of autocorrelation among disturbances. As per the above discussion, the lag order ρ of the panel VECM-based causality tests is computed to be one. The Hansen test statistic for the aluminum consumption equation is 0.296, while for the economic growth equation, it is 0.232. These generally adhere to the proposition of Roodman (2009), whereby the telltale sign of valid instruments is a high *p* value of the Hansen *J* statistic of 0.25. The H_0 of valid instruments in use is therefore accepted. It is equally essential to check the validity of subsets instruments at levels and differenced instruments. The difference-in-Hansen test of exogeneity is conducted under the null that the instruments in use are proper instruments, i.e., they are exogenous. The test assesses the system GMM with and without a subset of instruments to allow investigation about the validity of such subset of instruments, while considering their contribution to the rise in the Hansen *J* test statistic. These are denoted as the ‘‘Hansen Test Excluding Group’’ and ‘‘Difference (null H = exogenous),’’ respectively, under specific sub-headings. The H_0 of exogeneity of any system GMM instruments, used such as levels and differenced instruments, cannot be rejected.

Unidirectional causality running from aluminum consumption to economic growth is uncovered in the short-run, while economic growth is found to Granger-cause aluminum consumption in the long-run. A change in economic growth has an impact on aluminum consumption for individual high-income countries such as Australia, Austria, Belgium, etc., as well as for the panel as a whole in the long-run.

Table 13. Blundell–Bond System GMM Panel VAR Causality Test

Variables	$\Delta LALC_{it}$	$\Delta LGDP_{it}$
$\Delta LALC_{it-1}$	0.4427508 (0.2699059)	0.0717245 (0.0294157)**
$\Delta LGDP_{it-1}$	0.6644224 (1.227443)	0.544312 (0.1610004)*
ECT_{it-1}	−0.1621966 (0.0798776)**	−0.0355584 (0.046684)
Constant	−0.0035176 (0.0424829)	0.0077492 (0.0064156)
Observations	740	740
Number of Instruments	20	20
Sargan test of over-identifying restrictions	35.46 [0.003]*	69.39 [0.000]*
Hansen test of over-identifying restrictions	18.49 [0.296]	19.74 [0.232]
Difference-in-Hansen test of exogeneity of instrument subsets		
Instruments for levels		
Hansen test excluding group	18.47 [0.239]	19.70 [0.184]
Difference (null H = exogenous)	0.02 [0.882]	0.04 [0.846]
Instruments for GMM-style		
Hansen test excluding group	18.31 [0.193]	19.70 [0.140]
Difference (null H = exogenous)	0.18 [0.913]	0.04 [0.981]
AR(1) test of serial correlation	−1.90 [0.057]‡	−2.56 [0.010]‡
AR(2) test of serial correlation	1.38 [0.166]	0.58 [0.564]
Short-run causality test	0.29 [0.5883]	5.95 [0.0148]**
Long-run causality test	4.12 [0.0423]**	0.58 [0.4462]

The model is estimated by the two-step system GMM. The robust standard errors are in parenthesis while p-values are in square brackets. The log of population density and time dummies are used as ‘‘IV’’ instruments. These are not part of the VECM structure (e.g., Mileva 2007). The explanatory variables are assumed to be endogenous and their lags are instrumented in GMM-style (Roodman 2006).
Source Computed.

Table 14. Long-Run Estimates

	Long-Run Estimators			
	FMOLS		DOLS	
Variable	Coefficient	t-Statistics	Coefficient	t-Statistics
$LGDP_{it}$	0.45	15.80*	0.44	16.73*

The critical values of the two-tailed t-statistics test at 1, 5, and 10% significance levels are 2.326, 1.645, and 1.282, respectively. For the FMOLS, the selection of bandwidth for kernels is automatically computed while the maximum lag and leads for the DOLS is set to 2 (Nelson and Donggyu 2003). Wooldridge (2002) test of H_0 of no autocorrelation in panel data is $F(1,19) = 21.199$ [0.0002]*. This implies the existence of serial correlation. Moreover, Greene (1993) test of H_0 of homoskedasticity in fixed-effects panel data model is $\chi^2(703) = 1752.24$ [0.0000]*. This implies the prevalence of heteroskedasticity.
Source Computed.

Having determined the direction of the causal effects, the long-run impact of income elasticity of aluminum can next be estimated.

Long-Run Elasticities

Long-run elasticities can be obtained by means of either the fully modified OLS (FMOLS) or dynamic OLS (DOLS) panel data techniques which control for endogeneity, autocorrelation, and heteroskedasticity of residuals. The DOLS tends to outperform the FMOLS estimators in term of mean biases (Kao and Chiang 2000). For comparison purposes, both estimators are computed. Given evidence of cross-sectional dependence, the models include common time dummies (Pedroni 2001). As reported in Table 14, the income elasticities computed by the panel FMOLS and DOLS are quite similar. These are 0.45 and 0.44, respectively. In effect, aluminum is a necessity in the long-run.

CONCLUSION AND POLICY IMPLICATIONS

The article attempts to examine the link between aluminum consumption and economic growth for 20 rich countries over the period of 1970–2009. Two generations of panel unit root and cointegration tests are applied. Both series are found to be $I(1)$ cointegrated especially after controlling for cross-sectional dependence. A panel causality test in a VECM setting is next conducted using the Blundell–Bond system GMM. Unidirectional causality from aluminum consumption to real GDP is found in the short-run while real GDP is found to Granger-cause aluminum consumption in the long-run. Moreover, a 1% rise in real GDP causes a 0.44% rise in aluminum consumption in the long-run for the whole panel.

The prevalence of a long-run causal effect running from economic growth to aluminum consumption and a positive long-run income elasticity points to the importance of economic growth in driving the demand for aluminum. The absence of feedback effects reveals the importance of growth of real income in stimulating the demand for aluminum. These results are consistent with those of Ghosh (2006) and Huh (2011). In similar fashion, they have important implications for environmental and natural resource policies. For instance, various market actors and stakeholders can use these findings to make long-run assessments of aluminum consumption which is intrinsically linked with economic growth.

The aluminum sector is facing major challenges. Many smelting industries rely on power plants producing electricity via carbon-intensive input materials such as coal. There is thus a pressing a need for some form of government intervention. While the imposition of a carbon tax may be a solution to these ecologically harmful manufacturing practices, this can lead to smelter redundancy due to the rise in production cost. Job losses are another potential outcome.[6] Although the effect of a fall in aluminum consumption arising from a carbon tax may have only short-run impacts, policies should be enacted to preserve the future of the industry. For instance, many high-income countries, such as the European

[6]Rio Tinto has been forced to reduce its aluminium production due to the rise in cost arising from carbon tax although it claims to be using clean technology. More details are available online at http://www.themercury.com.au/article/2011/10/19/269911_tasmania-news.html.

Union (EU) members, have decided to introduce stricter CO_2 emission requirements for automobiles (T&E 2009), which may cause an increase in the demand for aluminum in the future. Aluminum is much lighter than steel, and this would enable cars to reduce fuel consumption and to emit less GHG emissions. It remains one of the most environmentally friendly metals and its recyclability is unlimited.[7] Government actions should therefore target the relevant externalities as precisely as possible.

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[7]More information can be accessed online at http://www.sapagroup.com/en/Company-sites/Sapa-Profiles-UK-Ltd/Aluminium/Recycling/.

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